Predictive Maintenance for Aircraft Engine using C-MAPSS Dataset

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THESIS PRESENTATION

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Introduction

- Predictive Maintenance (PdM) is a system which predict the condition of equipment of machines that are already in use this tells whether the maintenance is required or not. This technique ensures that cost-saving has done as compared to regular maintenance where unnecessary replacements have been done without proper utilization of resources.

- By taking Remaining Useful Life (RUL) into account the organizations can maintain, optimize operating efficiency, and also avoid unplanned downtime. Hence, estimating the remaining useful life (RUL) is the top priority in the Predictive Maintenance (PdM) program.

- Remaining Useful Life(RUL) is the estimated time at which system or a component will no longer perform its intended function.

Dataset Description

- The Dataset taken for this purpose is Damage Propagation Modelling for Aircraft Engine Run-to-Failure Simulation.
- NASA has created the Prognostics and Health Management PHM08 ***Challenge Data Set and is being made publicly available***.
- For the creation for dataset they uses the simulation tool called ***C-MAPSS*** (Commercial Modular Aero-Propulsion System Simulation). Which is used to a large amount of realistic commercial turbofan engines dataset.
- The sensor data has been fetched from 100 engines of the same model.
- Sensor noise has been detected in the collected data.
- Data sets consists of multiple multivariate time series
- A Multivariate time series has more than one time-dependent variable.

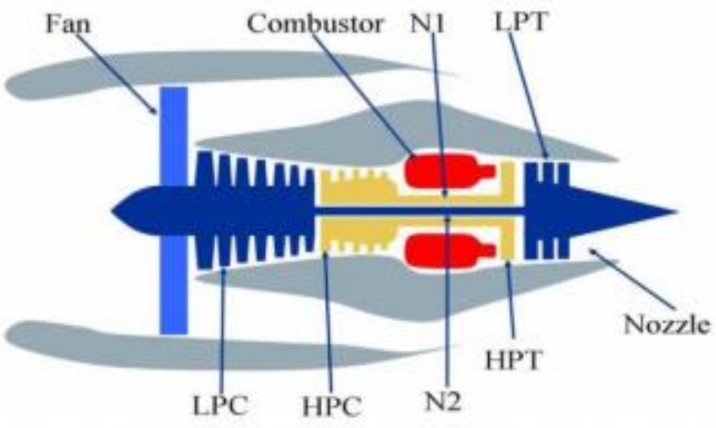


Fig-2: Schematic Of The Engine [7]

- The engine is operating normally at the start of each time series, and develops a fault at some point during the series.
- In the training set, the fault grows in magnitude until system failure.
- In the test set, the time series ends some time prior to system failure.
- The objective is to predict the number of remaining operational cycles before failure in the test set. Also provided a vector of true Remaining Useful Life (RUL) values for the test data.
- The data are provided text file with 26 columns of numbers, separated by spaces. Each row is a snapshot of data taken during a single operational cycle, each column is a different variable. The columns correspond to:

1) unit number
2) time, in cycles
3) operational setting 1
4) operational setting 2
5) operational setting 3
6) sensor measurement 1
7) sensor measurement 2...
8) sensor measurement 26

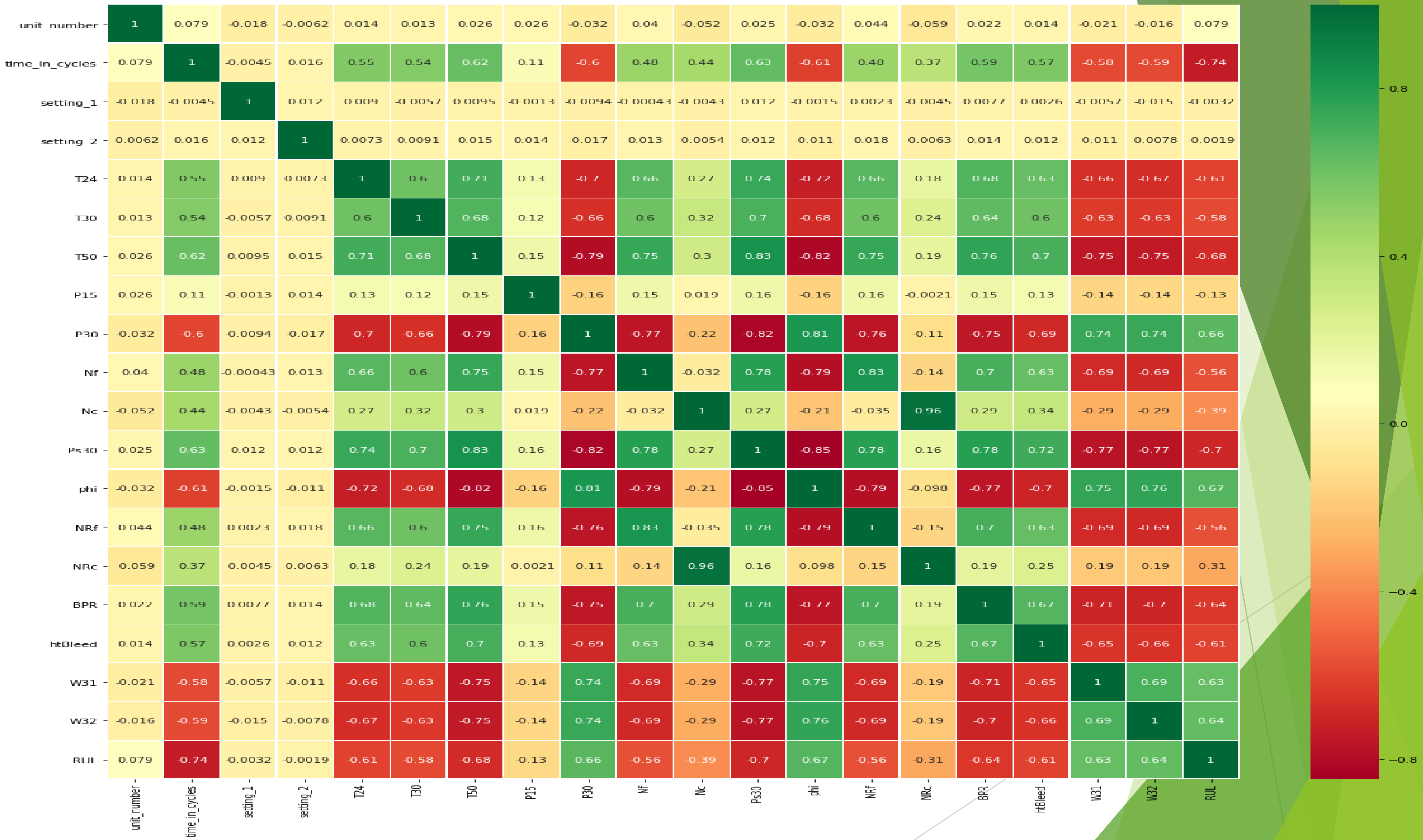
Symbol	*Description*	*Units*
Parameters available to participants as sensor data		
T2	Total temperature at fan inlet	°R
T24	Total temperature at LPC outlet	°R
T30	Total temperature at HPC outlet	°R
T50	Total temperature at LPT outlet	°R
P2	Pressure at fan inlet	psia
P15	Total pressure in bypass-duct	psia
P30	Total pressure at HPC outlet	psia
Nf	Physical fan speed	rpm
Nc	Physical core speed	rpm
epr	Engine pressure ratio (P50/P2)	--
Ps30	Static pressure at HPC outlet	psia
phi	Ratio of fuel flow to Ps30	pps/psi
NRf	Corrected fan speed	rpm
NRc	Corrected core speed	rpm
BPR	Bypass Ratio	--
farB	Burner fuel-air ratio	--
htBleed	Bleed Enthalpy	--
Nf_dmd	Demanded fan speed	rpm
PCNfR_dmd	Demanded corrected fan speed	rpm
W31	HPT coolant bleed	lbm/s
W32	LPT coolant bleed	lbm/s

Fig. 1. Different types of sensors used to record the data [1].

Data preprocessing

- There are total 26 columns named ('unit_number','time_in_cycles','setting_1','setting_2','TRA','T2','T24','T30','T50','P2','P15','P30',’Nf’ ,Nc','epr','Ps30','phi','NRf','NRc','BPR','farB','htBleed','Nf_dmd','PCNfR_dmd','W31','W32’)
- The columns which has constant values that do not carry information about the state of the unit are droped. ('Nf_dmd','PCNfR_dmd','P2','T2','TRA','farB','epr’)
- Now, the data has been grouped as per there respective Machine Id columns.
- Than feature correlation map has been used and We remove the properties that weakly correlate with the RUL target: setting_1, setting_2, P15, unit_number, as well as one of the features that are highly correlated with each other (Nc and NRc have a correlation coefficient of 0.96, remove NRc), Than are final preprocessed data looks like below.

	time_in_cycles	T24	T30	T50	P30	Nf	Nc	Ps30	phi	NRf	BPR	htBleed	W31	W32	RUL
0	1	641.82	1589.70	1400.60	554.36	2388.06	9046.19	47.47	521.66	2388.02	8.4195	392	39.06	23.4190	191
1	2	642.15	1591.82	1403.14	553.75	2388.04	9044.07	47.49	522.28	2388.07	8.4318	392	39.00	23.4236	190
2	3	642.35	1587.99	1404.20	554.26	2388.08	9052.94	47.27	522.42	2388.03	8.4178	390	38.95	23.3442	189
3	4	642.35	1582.79	1401.87	554.45	2388.11	9049.48	47.13	522.86	2388.08	8.3682	392	38.88	23.3739	188
4	5	642.37	1582.85	1406.22	554.00	2388.06	9055.15	47.28	522.19	2388.04	8.4294	393	38.90	23.4044	187


unit_number 1 0.079 -0.018 -0.0062 0.014 0.013 0.026 0.026 -0.032 0.04 -0.052 0.025 -0.032 0.044 -0.059 0.022 0.014 -0.021 -0.016 0.079
time_in_cycles 0.079 1 -0.0045 0.016 0.55 0.54 0.62 0.11 -0.6 0.48 0.44 0.63 -0.61 0.48 0.37 0.59 0.57 -0.58 -0.59 -0.74
setting_1 -0.018 -0.0045 1 0.012 0.009 -0.0057 0.0095 -0.0013 -0.0094 -0.00043 -0.0043 0.012 -0.0015 0.0023 -0.0045 0.0077 0.0026 -0.0057 -0.015 -0.0032
setting_2 -0.0062 0.016 0.012 1 0.0073 0.0091 0.015 0.014 -0.017 0.013 -0.0054 0.012 -0.011 0.018 -0.0063 0.014 0.012 -0.011 -0.0078 -0.0019
T24 0.014 0.55 0.009 0.0073 1 0.6 0.71 0.13 -0.7 0.66 0.27 0.74 -0.72 0.66 0.18 0.68 0.63 -0.66 -0.67 -0.61
T30 0.013 0.54 -0.0057 0.0091 0.6 1 0.68 0.12 -0.66 0.6 0.32 0.7 -0.68 0.6 0.24 0.64 0.6 -0.63 -0.63 -0.58
T50 0.026 0.62 0.0095 0.015 0.71 0.68 1 0.15 -0.79 0.75 0.3 0.83 -0.82 0.75 0.19 0.76 0.7 -0.75 -0.75 -0.68
P15 0.026 0.11 -0.0013 0.014 0.13 0.12 0.15 1 -0.16 0.15 0.019 0.16 -0.16 0.16 -0.0021 0.15 0.13 -0.14 -0.14 -0.13
P30 -0.032 -0.6 -0.0094 -0.017 -0.7 -0.66 -0.79 -0.16 1 -0.77 -0.22 -0.82 0.81 -0.76 -0.11 -0.75 -0.69 0.74 0.74 0.66
Nf 0.04 0.48 -0.00043 0.013 0.66 0.6 0.75 0.15 -0.77 1 -0.032 0.78 -0.79 0.83 -0.14 0.7 0.63 -0.69 -0.69 -0.56
Nc -0.052 0.44 -0.0043 -0.0054 0.27 0.32 0.3 0.019 -0.22 -0.032 1 0.27 -0.21 -0.035 0.96 0.29 0.34 -0.29 -0.29 -0.39
Ps30 0.025 0.63 0.012 0.012 0.74 0.7 0.83 0.16 -0.82 0.78 0.27 1 -0.85 0.78 0.16 0.78 0.72 -0.77 -0.77 -0.7
phi -0.032 -0.61 -0.0015 -0.011 -0.72 -0.68 -0.82 -0.16 0.81 -0.79 -0.21 -0.85 1 -0.79 -0.098 -0.77 -0.7 0.75 0.76 0.67
NRf 0.044 0.48 0.0023 0.018 0.66 0.6 0.75 0.16 -0.76 0.83 -0.035 0.78 -0.79 1 -0.15 0.7 0.63 -0.69 -0.69 -0.56
NRc -0.059 0.37 -0.0045 -0.0063 0.18 0.24 0.19 -0.0021 -0.11 -0.14 0.96 0.16 -0.098 -0.15 1 0.19 0.25 -0.19 -0.19 -0.31
BPR 0.022 0.59 0.0077 0.014 0.68 0.64 0.76 0.15 -0.75 0.7 0.29 0.78 -0.77 0.7 0.19 1 0.67 -0.71 -0.7 -0.64
htBleed 0.014 0.57 0.0026 0.012 0.63 0.6 0.7 0.13 -0.69 0.63 0.34 0.72 -0.7 0.63 0.25 0.67 1 -0.65 -0.66 -0.61
W31 -0.021 -0.58 -0.0057 -0.011 -0.66 -0.63 -0.75 -0.14 0.74 -0.69 -0.29 -0.77 0.75 -0.69 -0.19 -0.71 -0.65 1 0.69 0.63
W32 -0.016 -0.59 -0.015 -0.0078 -0.67 -0.63 -0.75 -0.14 0.74 -0.69 -0.29 -0.77 0.76 -0.69 -0.19 -0.7 -0.66 0.69 1 0.64
RUL 0.079 -0.74 -0.0032 -0.0019 -0.61 -0.58 -0.68 -0.13 0.66 -0.56 -0.39 -0.7 0.67 -0.56 -0.31 -0.64 -0.61 0.63 0.64 1
unit_number time_in_cycles setting_1 setting_2 T24 T30 T50 P15 P30 Nf Nc Ps30 phi NRf NRc BPR htBleed W31 W32 RUL
0.8
0.4
0.0
−0.4
−0.8

Proposed methodology

- We are not only giving the regressor models for prediction of Remaining Useful Life but also the classification models to determine whether the present cycle of the engine is in a healthy state or is about to fail sooner (proactively).
- So, We have two methods:

1) Methodology for Remaining Useful Life (RUL)
    1. Overall Training & Prediction at one time.
    2. Individual Prediction & Training (Single Train).
    3. Average of last 5 cycles prediction.
    4. Average of last 10 cycles prediction.
2) Methodology for Classification Model
    1. Random Forest Classifier.
    2. Xgboost Classifier.

Methodology for Remaining Useful Life (RUL)

- ***Overall Training & Prediction at one time.***

Entire Data has been given to models for training at one go only and than the prediction has been taken out.

- ***Individual Prediction & Training (Single Train).***

Entire Data has been grouped by machine-id and the grouped data has been given to model one by one and simultaneously the prediction has been taken out w.r.t its machine id.

- ***Average of last 5 cycles prediction.***

The training is similar to Single train method but the prediction is done for last 5 cycles of individual machine and there average is taken out.

- ***Average of last 10 cycles prediction.***

The training is similar to Single train method but the prediction is done for last 10 cycles of individual machine and there average is taken out.

Workflow Diagram

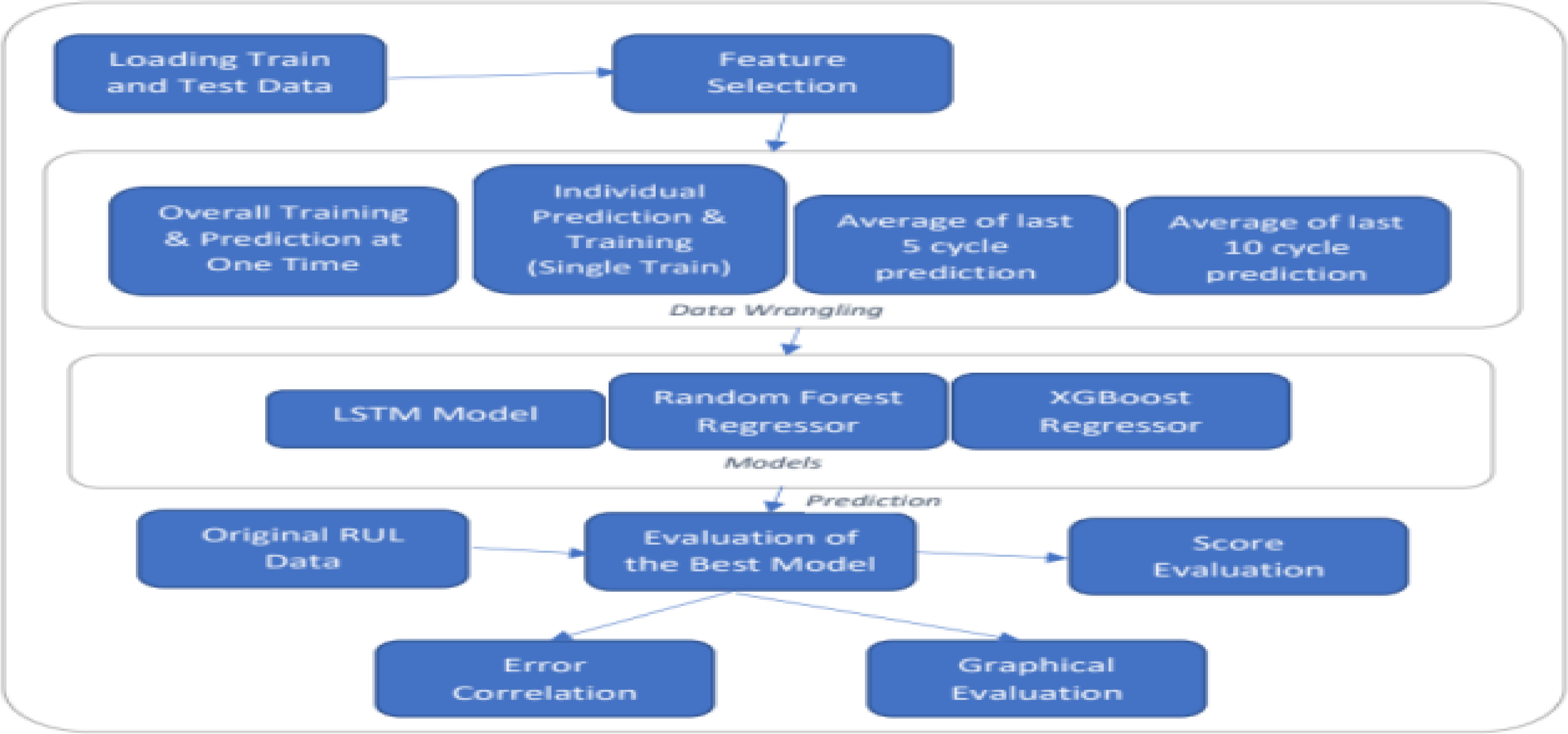


Fig. 2. Workflow of Remaining Useful life (RUL).

Method 1. Overall Training & Prediction at one time.

Method 2. Individual Prediction & Training (Single Train).

Method 3. Average of last 5 cycles prediction.

Method 4. Average of last 10 cycles prediction.

Long Short-Term Memory (LSTM)	Random Forest Regressor	Xgboost Regressor
Method 1	Method 1	Method 1
-	Method 2	Method 2
-	Method 3	Method 3
-	Method 4	-

Table 1. Data Wrangling Methods for different models. [16]

Methodology for Classification Model

- classification models to determine whether the present cycle of the engine is in a healthy state or is about to fail sooner (proactively).
- This approach answer the question “Current engine resources will last more or less than 10 cycles?”. By classification models
- It’s assumed that 10 cycles are sufficient to prepare and start maintenance.
- Two Model has been applied on this approach these are
- Random Forest Classifier
- Xgboost Classifier

Workflow Diagram

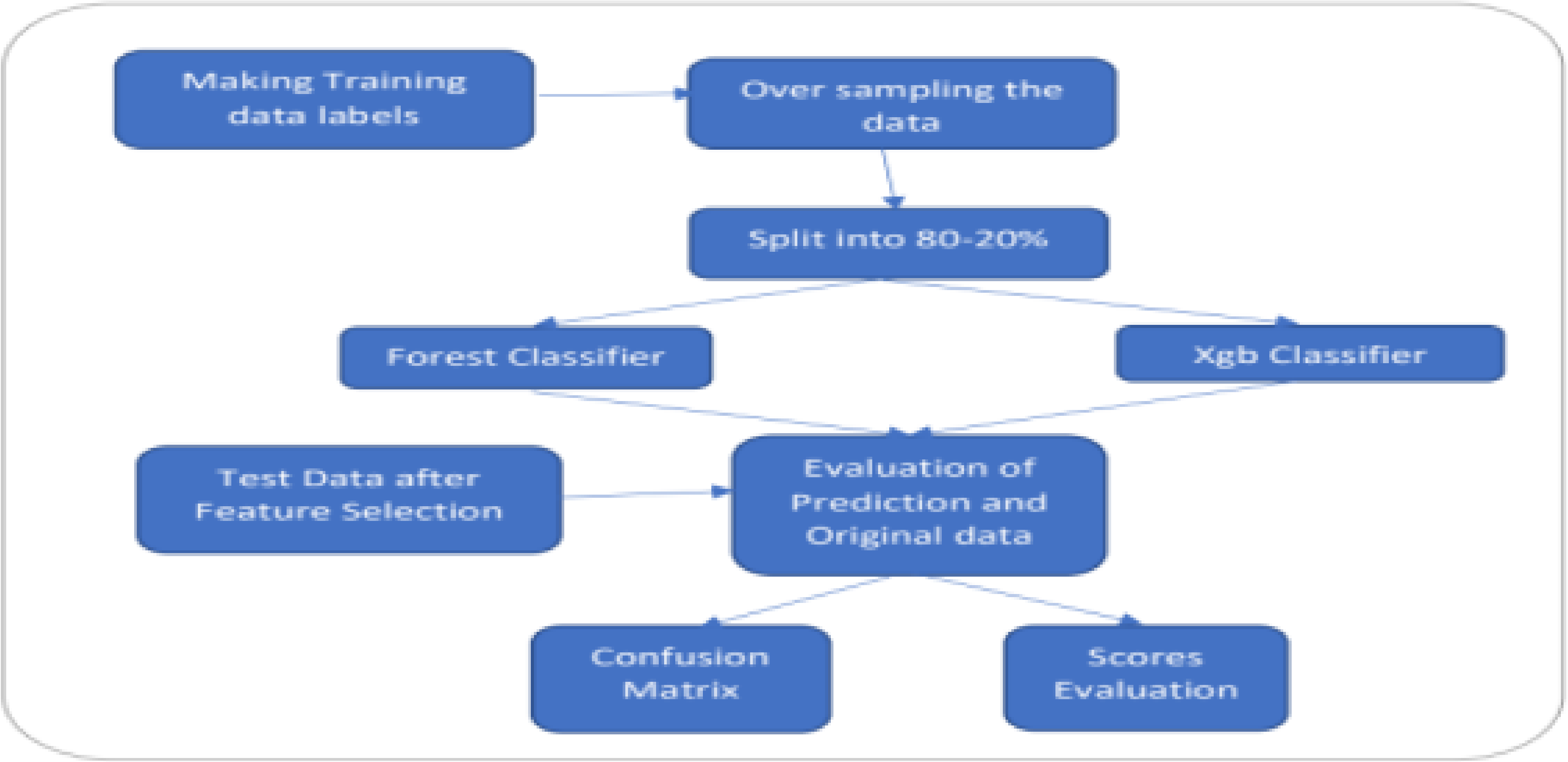


Fig. 3. Workflow of Classifiers.

Result & Analysis

Remaining Useful Life (RUL) Models Evaluation

Method-1: Overall Training & Prediction at One Time.

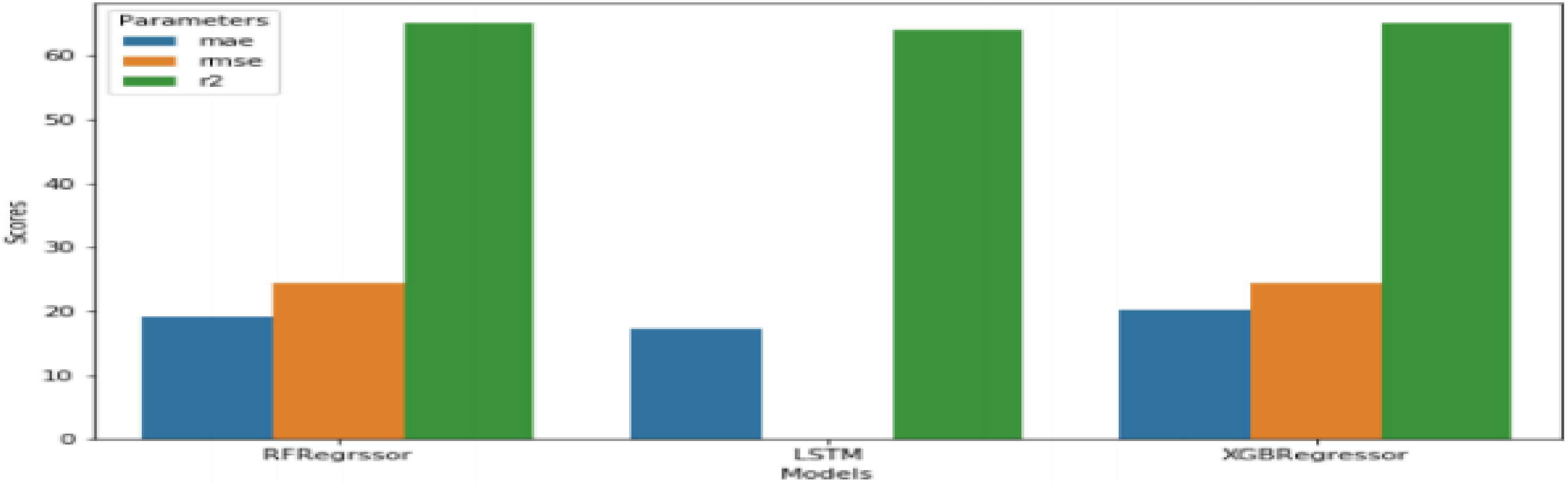


Fig. 6. Bar graph evaluation on three parameters (R2 Score, RSME, MAE) of three models.

	Long Short-Term Memory (LSTM)	Random Forest Regressor	Xgboost Regressor
Competitive Score	-	1057.2	1168.04
Mean Absolute Error	17.38	19.25	20.32
Root Mean Square Error	-	24.45	24.54
R2 Score	64.00	65.00	65.00

Table 2. Tabular Explanation of various parameter from different models

Here the blue line is prediction line and the orange is the actual line of data.

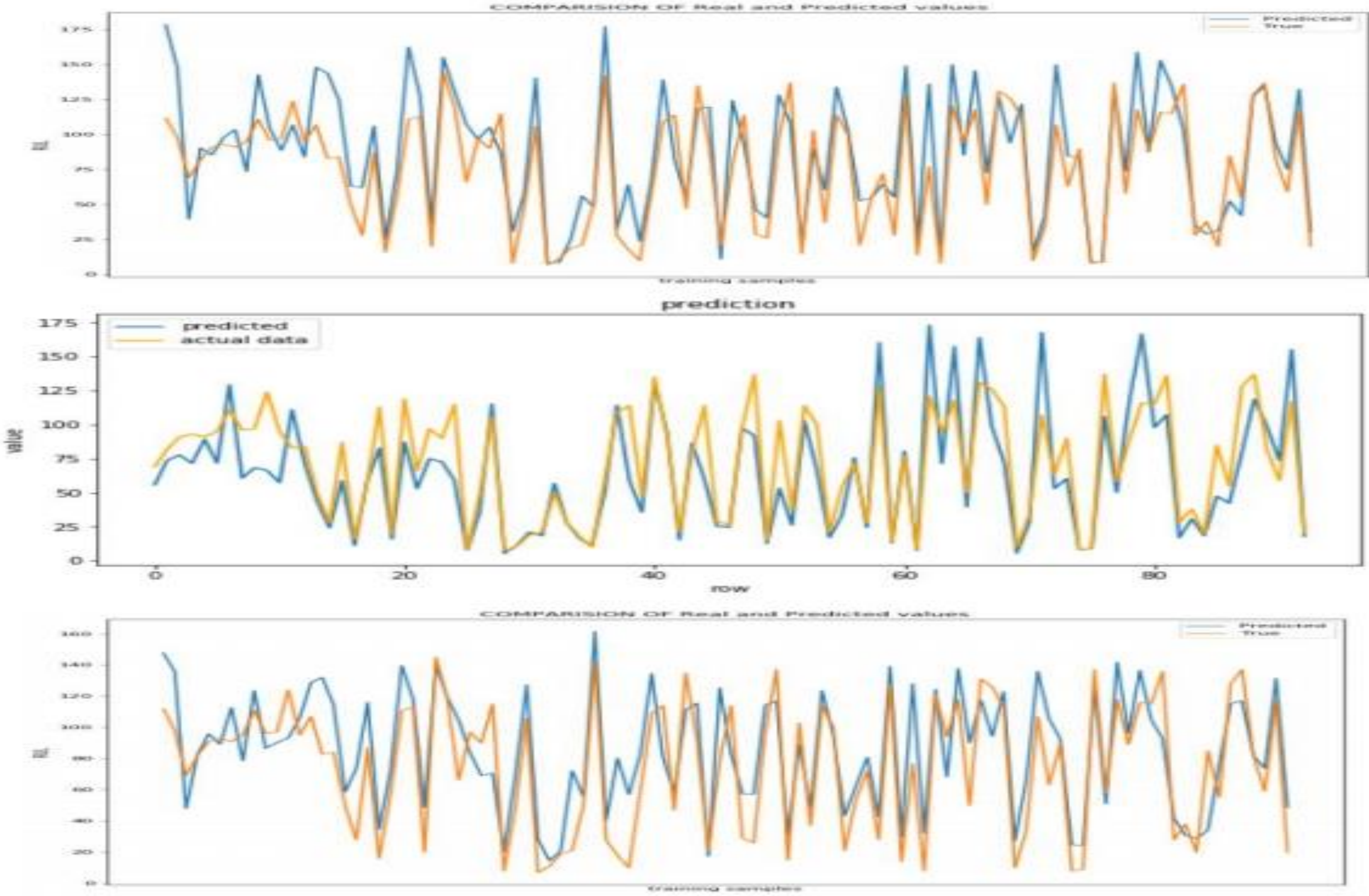


Figure 5.2. True value comparison with prediction values of random forest regressor, Long sort termed memory (LSTM) model and Xgboost regressor model respectively.

Method-2: Individual Prediction & Training (Single Train).

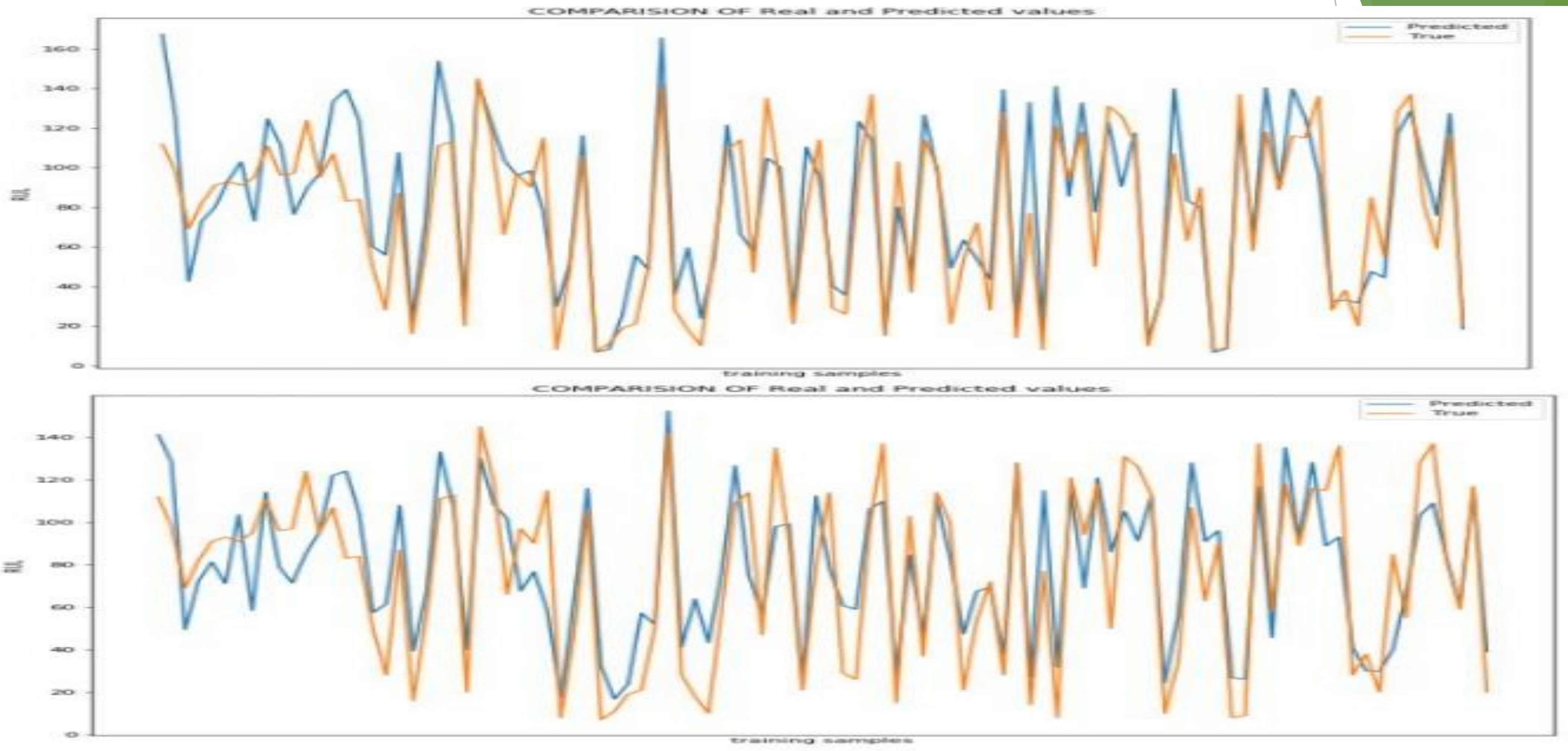


Fig. 7. True value comparison with prediction values of random forest regressor model and Xgboost regressor model respectively.

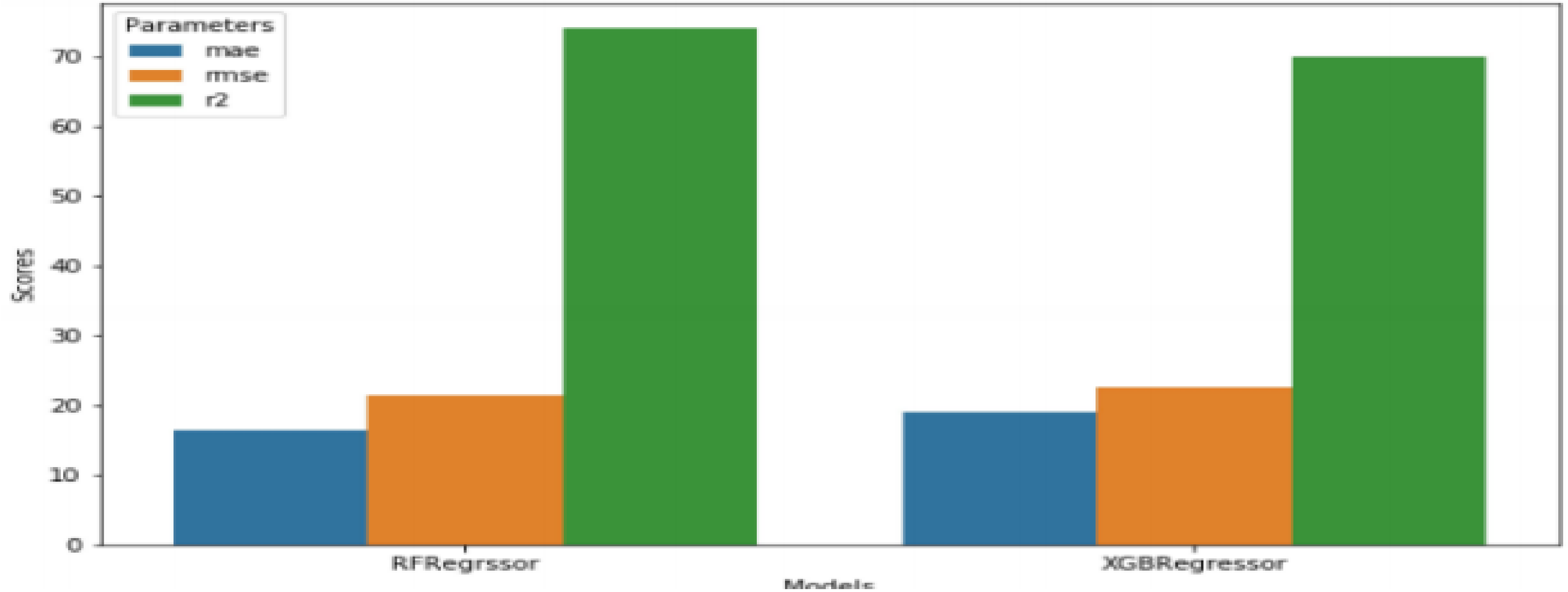


Fig. 8. Bar graph evaluation on three parameters (R2 Score, RSME, MAE) of two models.

	Random Forest Regressor	Xgboost Regressor
Competitive Score	868.02	1151.70
Mean Absolute Error	16.49	18.97
Root Mean Square Error	21.34	22.65
R2 Score	74.00	70.00

Table 3. Tabular Explanation of various parameter from different models

Method-3: Average of last 5 cycle predictions.

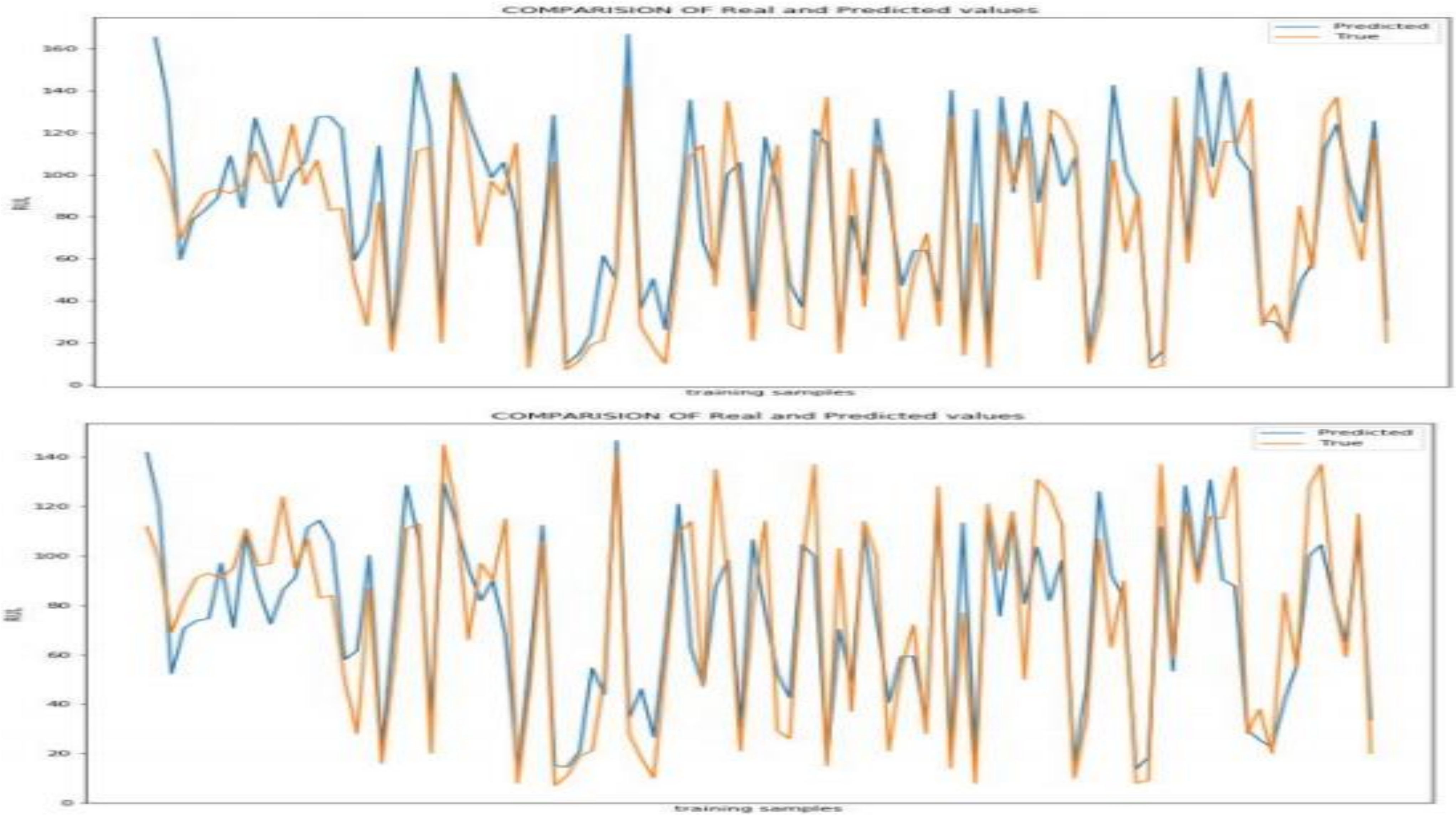


Fig. 10. True value comparison with prediction values of random forest regressor model and Xgboost regressor model respectively.

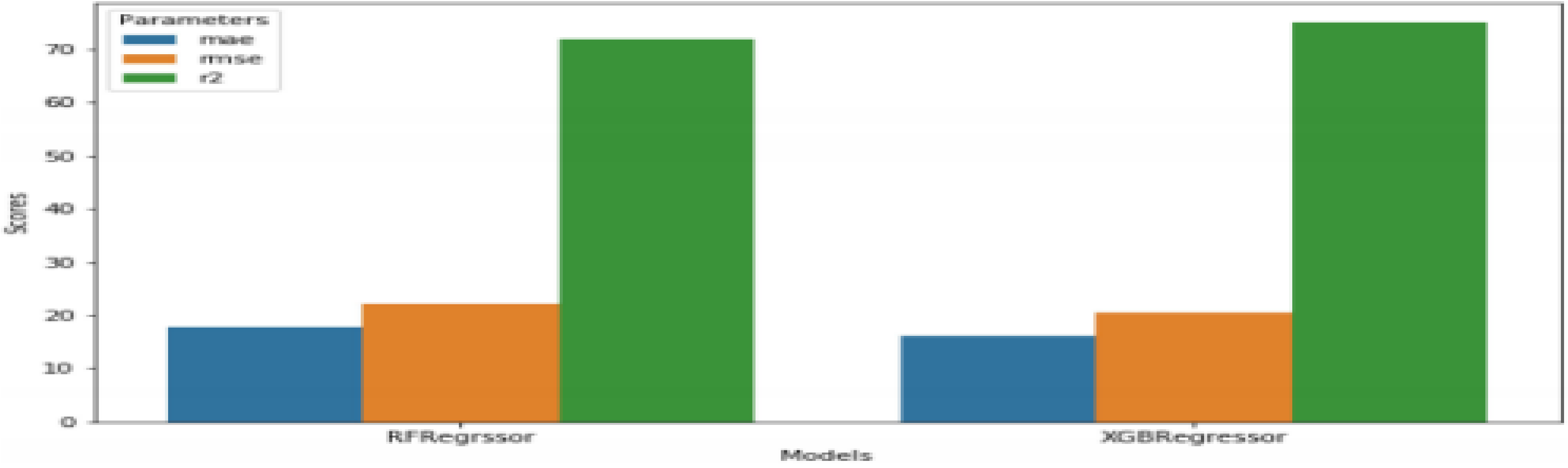


Fig. 9. Bar graph evaluation on three parameters (R2 Score, RSME, MAE) of two models.

	Random Forest Regressor	Xgboost Regressor
Competitive Score	810.53	1140.62
Mean Absolute Error	17.78	16.07
Root Mean Square Error	22.17	20.58
R2 Score	72.00	75.00

Table 4. Tabular Explanation of various parameter from different models

Method-4: Average of last 10 cycle predictions.

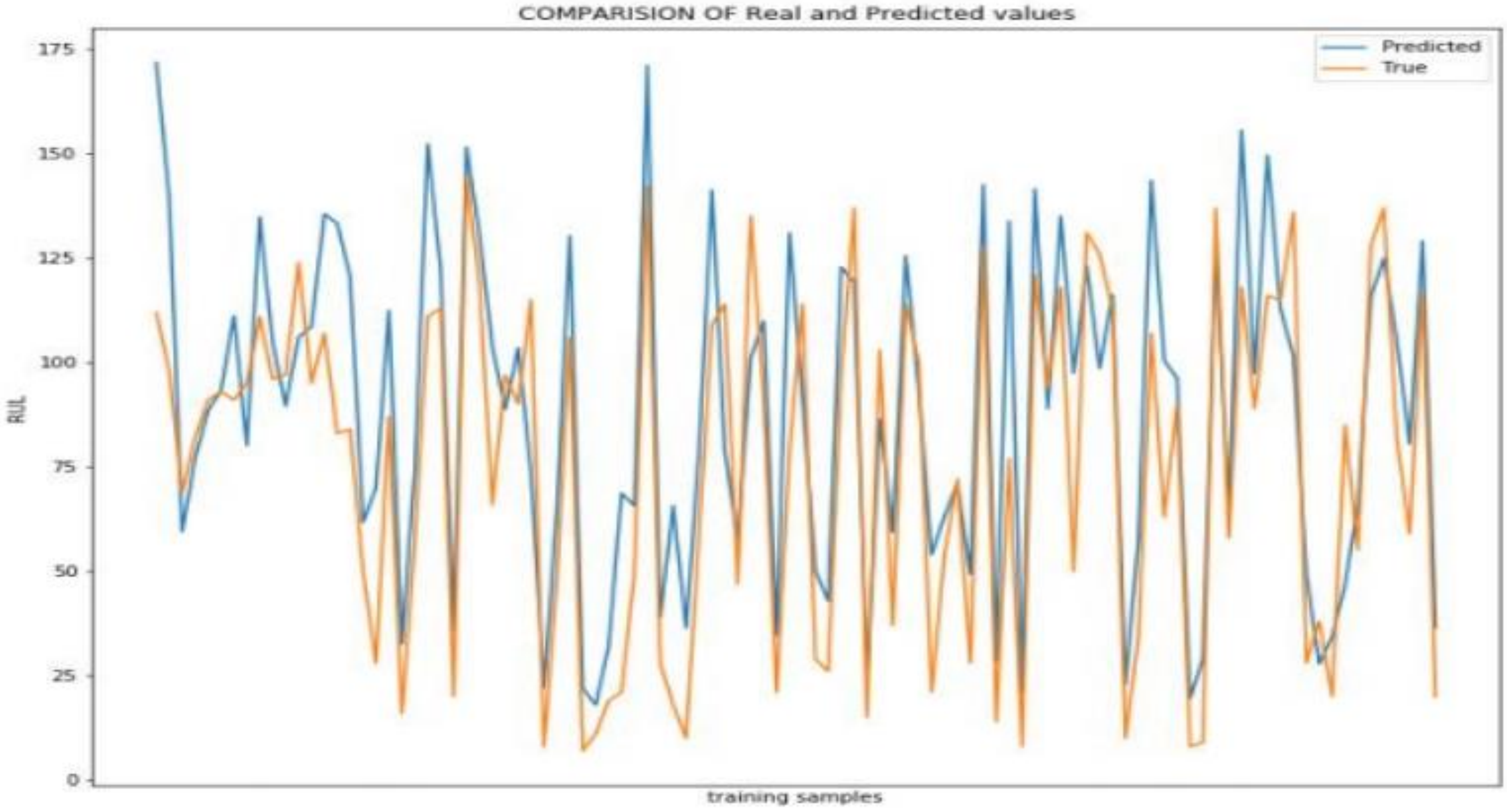


Fig. 11. True value comparison with prediction values of random forest regressor model and Xgboost regressor model respectively.

	Random Forest Regressor
Competitive Score	990.42
Mean Absolute Error	20.55
Root Mean Square Error	24.55
R2 Score	65.00

Table 5. Tabular Explanation of various parameter from different models

4.1.5. Comparing the forecast of all models and its error deviation with original values.

Classification Models Evaluation

	Random Forest Regressor	Xgboost Regressor
Accuracy Score	0.98	0.98
Pression Score	0.96	0.97
Recall Score	1.0	1.0
F1 Score	0.98	0.98

Table 6. Comparative Score Table of Classification Models

	forest	XGB	RUL	true_label	unit_number
34	1	1	11	0	35
35	1	0	19	0	36
48	1	0	21	0	49
55	1	1	15	0	56

Fig. 13. Engines for which Random Forest Classifier gives an incorrect prediction

	forest	XGB	RUL	true_label	unit_number
19	0	1	16	0	20
34	1	1	11	0	35
55	1	1	15	0	56
67	1	0	8	1	68
81	1	0	9	1	82

Fig. 14. Engines for which Xgboost Classifier gives an incorrect prediction

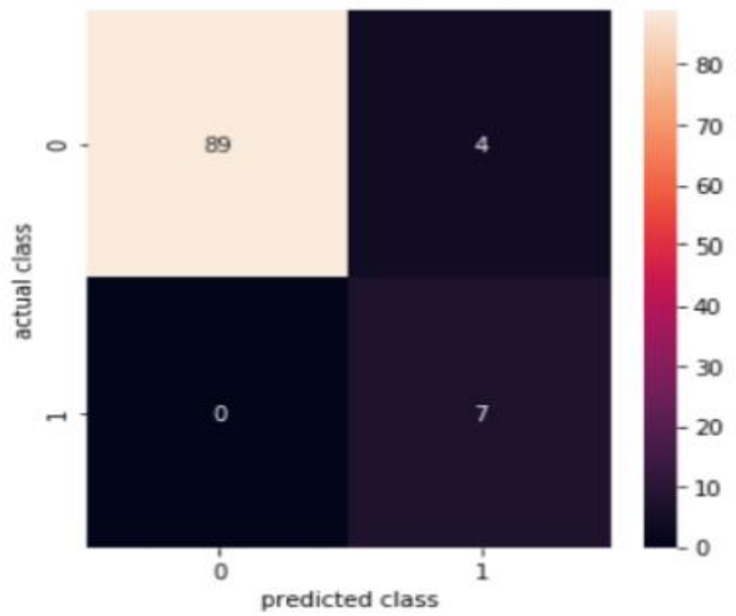


Fig. 15. Confusion Matrix for Random Forest

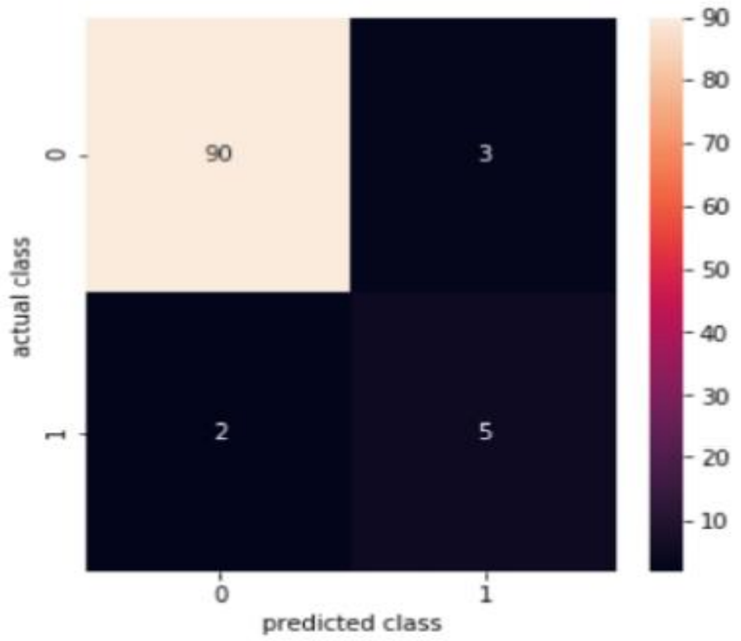


Fig. 16. Confusion Matrix for Xgboost

	Random Forest Classifier	Xgboost Classifier
True Positive	7	5
True Negative	89	90
False Negative	3	2
False Positive	0	2

Table 7. Confusion Matrix in Tabular form

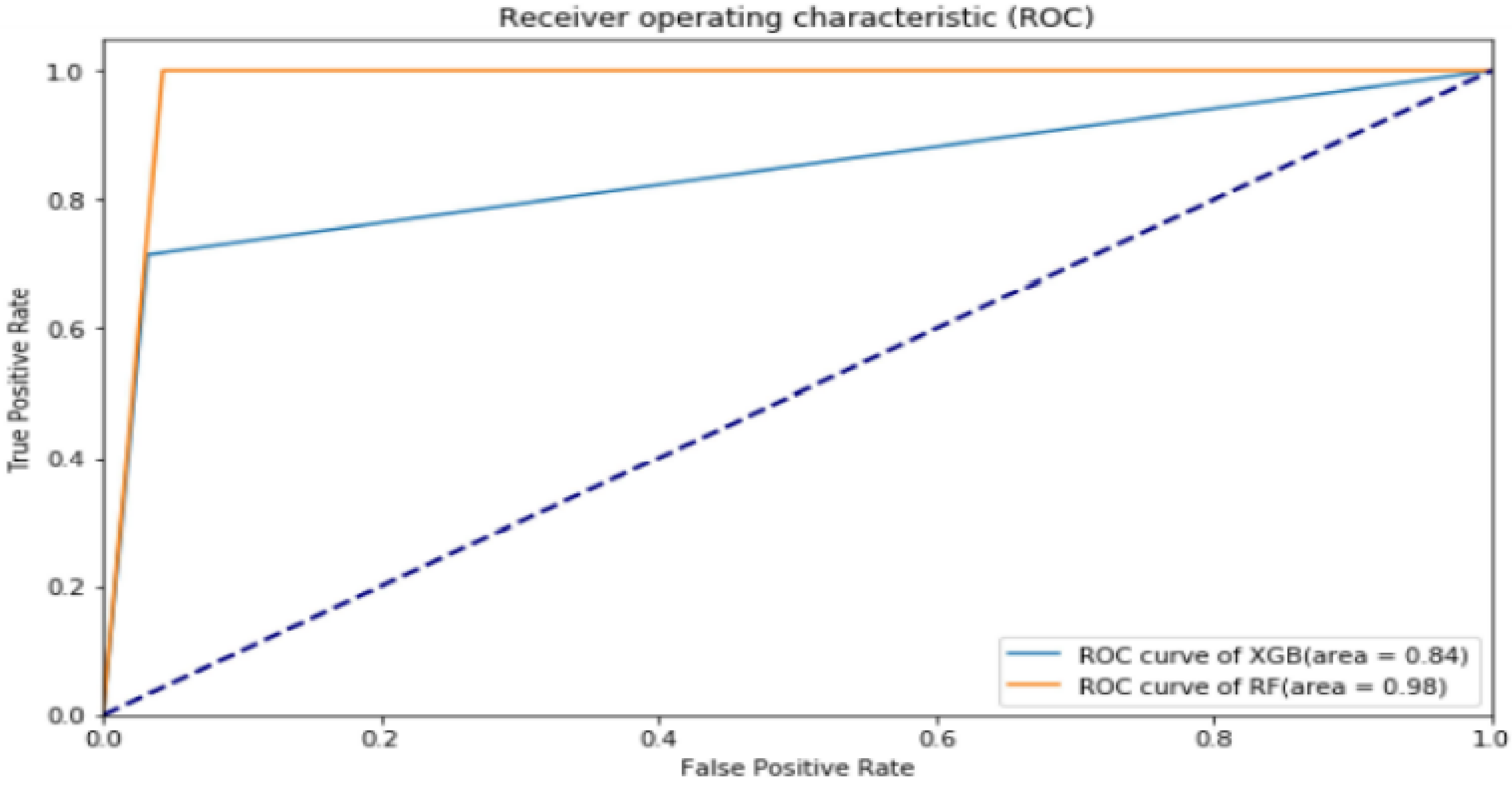


Fig. 17. Receiver Operating Characteristics (ROC) for evaluating the performance for both the classifiers.

Conclusion

- The proposed classification algorithms show useful results on test data and can be used to obtain cost savings during preventive maintenance of aircraft engines, to estimate the approximate remaining engine life (if the corresponding error is permissible under specific conditions) it can be used in conjunction with the regression algorithms described above.

- For Remaining Useful Life (RUL) model the average of the *last 5 cycles predictions Approach* gives better results whereas on the other hand for classification *Both the classifier* performed almost the same.

- It's important to note that the user may use the blending of all the models to generate more strong results. And also, use a different dataset with the same approach but this may result in different accuracy or different best model.

References

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Thank You